OPERATIONS RESEARCH IN MARKETING: WHAT'S UP*

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Abstract

Quantitative methods in marketing are selectively reviewed. Emphasis is placed on data-based models useful for decision making within the individual firm and on measurement techniques to support such models. First the functional areas, advertising, sales force, distribution channels, pricing, and new products are reviewed. Then progress toward the design and analysis of marketing systems is discussed. Significant trends in the development of quantitative methods in marketing are found to be: increased complexity, greater use of data based models, inclusion of subjective judgments into models, new measurement techniques, adaptive and behavioral models, and the use of on-line computation.

The exponential growth of quantitative methods in marketing manifests itself in the published literature, in business, and in the universities. Five years ago it took a good deal of scrabbling around to collect enough papers for the book, Mathematical Models and Methods in Marketing [7]. Today we find two regular journals, The Journal of Marketing Research (age 2 years) and the more specialized Journal of Advertising Research (age 5 1/2 years), both of which contain a good percentage of quantitative material. In addition, increasingly frequent marketing papers are appearing in Operations Research and Management Science, and isolated studies are to be found in an assortment of other places.

Several universities now have individuals or groups who are particularly interested in marketing models and their applications, for example: MIT, Wharton, Carnegie Tech, Stanford, and Northwestern. In business, of course, there has been a parallel development. Companies are a good deal less talkative than academicians. Companies fancy (often incorrectly, I believe) that their livelihood depends on secrecy, whereas academicians fancy (correctly, I assure you) that their livelihood depends on being talkative. This situation will influence the material reported here. It will be biased toward published papers and toward my own particular word-of-mouth acquaintance with company work.

As the field grows, several important and quite desirable changes are taking place. To put them in perspective, let us examine some characteristics usually found in earlier work.

In many cases the researcher tried to abstract the essence of a problem and imbed it into a simple model. Simplicity was important to keep the

model manageable. Mathematical manipulations could then produce "optimal" values of marketing variables. Good examples of this type of work are the models of Mills [59] and Friedman [30] in advertising and Baumol and Ide [8] in retailing. The Mills and Friedman papers hypothesize, with certain variations, that a firm's market share depends on its share of total advertising expenditures. In Mills' case the individual expenditures are weighted by effectiveness coefficients. Using these models the competitive interaction among firms can be analyzed. The analysis leads to useful insights about how to allocate spending to markets, how one firm's spending may affect another's action, and how parameters such as gross margin and advertising effectiveness are likely to interact with spending and thence market share.

Baumol and Ide deal with variety in retailing. They hypothesize that a customer's willingness to shop at a store depends on his expectation of a successful purchase and on the difficulty of shopping. The probability of successful purchase depends in turn on the variety (number) of items carried by the store. The difficulty of shopping depends on the distance to the store and also on the variety of items that must be searched through. The consumer model generates demand for a retailer model. Demand, combined with the costs of stocking an item, produces a retailer profit model from which an optimal variety expression can be derived. Among other things, Baumol and Ide's work offers insight into why variety is likely to be advantageous up to a point and show diminishing returns thereafter and how this relationship will be affected by changes in certain types of costs.

Such models are valuable and we need more of them. They yield understanding and frequently will affect actions, but I think it is safe to say

that very few people plug numbers into the formulas. By and large, the assumptions are too sweeping, the data bases too small or entirely lacking, and the omitted variables too many to make the derived optimal policies real prescriptions for action. The interpretation and use of such models might be called the qualitative use of quantitative models. Ideas and relationships are stated and manipulated in symbols instead of words. This can, of course, be very valuable and indeed frequently is superior to doing the same things in words, since multiple interactions are often treated much more easily in symbols. The difficulties of translating the results into action are akin to those of translating a verbal theory into action. One must add judgment and additional information appropriate to the circumstances.

We are now witnessing, however, some new trends in marketing models that greatly broaden their scope and applicability:

1. Increased complexity. Models are being built with hundreds of marketing variables. Attempts are being made to describe, on a simulation basis, whole product markets.

2. Data based models. Thanks to the computer we are beginning to see large banks of marketing data and, at the same time, we have at hand the means of manipulating them. Models are being tested against data extensive enough to provide a good evaluation of the model. Furthermore, it has become reasonable in cost to update a complex model with new data on a regular basis.

3. Incorporation of subjective judgments into models. If you can't lick 'em, join 'em. Businessmen frequently seem to make better decisions than they have any right to on the basis of the available information.

An important step in model building, therefore, is to incorporate judgmental information directly into the model. One direction this has gone is represented by the extensive work on subjective probability, utility, and statistical decision theory. In another area, complex simulation models often require structures and parameters that are poorly known empirically. Researchers have worked with businessmen to develop parameter values and microscopic structures partly on judgmental and intuitive grounds.

4. New measurement techniques. Field experimentation, laboratory experimentation, and expanding commercial marketing data services are strengthening the empirical base on which to build models.

5. Adaptive models. The market does not stand still. Decisions that recur, e.g., budgeting and allocation of effort, can seldom be made and then forgotten. Models have been developed that produce rules rather than specific decisions. The rules process incoming data so as to adapt operations to changing conditions.

6. Behavioral models. Two developments are of particular interest. At the company level the study of how people and organizations make decisions is revealing heuristic problem solving procedures. At the consumer level attempts are under way to follow up and extend developments in the behavioral sciences so as to measure and model consumer behavior.

7. On-line computation. The advent of remote computer terminals with relatively immediate access to large machines is a technological breakthrough of great significance in many fields, not the least of which is marketing. First and most obvious, the process of writing and debugging of programs is speeded by a factor of 5 or 10, thus accelerating the whole

field of computation. Of more ultimate interest, however, are the opportunities for close interaction between model builder and data, decision maker and model. We shall cite some examples below.

Functional Areas

Let us look next at several marketing areas, broken down along conventional lines into advertising, sales force, distribution channels, pricing, and new products. We shall see that some of these areas have received more attention than others but that all show signs of activity. Our coverage will emphasize normative, data-based models and supporting measurement techniques. However, a few descriptive and theoretical studies will be mentioned.

Advertising. Advertising has been a particularly active area. It has been an area of pioneering work on direct field experimentation to measure the effect of marketing variables on sales. The excellent and accessible studies of Henderson, Hoofnagel and others [34, 35, 38, 40] at the Department of Agriculture are public examples. Their work has been broader than advertising, since they usually test several types of promotion at once. Examples of their work are:

1. A comparison of the sales of a product under the different promotional treatments: (1) special point of purchase advertising, (2) store demonstrations, (3) dealer contests, (4) media advertising, and (5) no promotion. See [38].

2. A comparison of the sales effect of (1) a regular promotional program involving media advertising, tie-in point of sale displays, and other supporting activities, (2) a program with cooperative advertising substituted for media advertising and (3) a control program without promotional activity. See [34].

3. A comparison of the sales effect of two themes for a promotional campaign: a product use theme and a health theme. See [35].

These experiemnts deal with agricultural products promoted by trade associations and sold through supermarkets. Formal experimental designs are used, usually Latin squares or some variation thereof. The experimental unit is a group of supermarkets in a city for a fixed period ot time, the number of experimental units ranging from 18 to 36 in the above instances. Analysis follows classical statistical lines. (For a recasting of one of the examples to illustrate a decision theoretic approach, see [51].)

A considerable number of companies have also run formal sales experiments. Usually, the purpose has been to measure advertising effects, particularly with respect to dollar level of expenditure or media effectiveness. The published work is slim and not necessarily representative. See, however, [9, 12 (Chapter 8), 19]. With respect to experimental design techniques, there is now a book oriented specifically to marketing in Banks [5].

The sales effects of advertising have been estimated by applying regression methods to historical data. Palda [63], Meissner [58], and Henderson and Brown [33] display examples. In TV, Buzzell [13], has

tried to show the sales effect of copy quality as measured by Schwerin theater tests. Regression of historical data is a difficult tool to use successfully, or, at least, without professional criticism. See [14, 26, 27, 28, 56, 62]. One central difficulty is that, in order to obtain measurements, something approximating test conditions must have occurred in the historical data. Such conditions are out of the hands of the researcher and, in fact, need not have existed in any satisfactory sense. A discussion of the pitfalls of econometric methods has been given by Quandt [66].

Media selection has been the focus of a good deal of effort and even more publicity. The problem at hand is to specify the time, place, intensity, and media type for a set of advertising insertions that, given a fixed budget, will maximize some specified measure of effectiveness. The measure of effectiveness has been variously defined but, for most writers, has been closely related to advertising exposures, weighted for the particular media vehicle of the exposure and for the sales potential of the audience exposed.

Starting from a provocative but reasonably untenable linear programming model [70, 12 (Chapter 5)], the field has seen a series of other mathematical models [11, 24, 42, 48, 49, 73], all with certain difficulties. the problems of diminishing returns with increasing exposure, duplication of media the timing of the insertions, the media discount structure, and the number of alternatives that can realistically be handled have not usually been well treated. These problems do not appear unsolvable. For a few suggestions, see [52]. In addition to the strictly mathematical programming models,

heuristic programming approaches are appropriate and have been used but too little information has been made public to evaluate their efficacy.

Media models require inputs that, as of today, are not available on an adequate empirical basis but about which people make judgments every day. Here is an obvious case where judgments about influence mechanisms and relative effectiveness can be abstracted from people, combined with data, and applied consistently by a computer to evaluate many times the number of alternative actions that can be done manually.

The readership of ads in print media has been studied to determine the effects of format variables. By format variables we mean size, number of colors, left or right page, headline prominence, page position, etc. Regressions have been run to relate measures of readership (e.g. Starch scores) with these variables. Diamond [22] explains 65% of the variance in 1070 Life ads. Trodahl and Jones [69] explain 61% of the variance in 1091 ads in the Minneapolis Morning Tribune. Yamanaka [72] explains 79% of the variance in 376 ads in the Nagoya Chubu-Nippon Shimbun. We must be careful not to equate readership with sales, but clearly readership is relevant and will be an input to more complex models of the advertising influence process. Diamond, incidentally, is ready for the regression critics, for he has run a validation study verifying the predictive power of his expressions on a set of ads not used in the construction of the expressions.

Diamond has also taken a step in an important and innovative direction. He has programmed the readership model for on-line use with the Project MAC computer system at MIT. The computer stores not only the model but

also data from which the cost of an ad can be calculated. A user can sit at a typewriter console, enter a set of variables specifying the ad format and obtain immediately the predicted ad readership. Alternatively he can obtain the readership/dollar spent or any of a variety of other evaluative criteria.

The user can do something else. He can specify just some of the variables and have the computer choose the remainder so as to maximize the specified criterion. One might ask, therfore, why not let the computer choose all the variables? The reason is that the readership model certainly does not include all the factors that should be considered in designing an ad. What we have here is an opportunity for a man-machine interaction combining the man's judgment and the model's data. Thus, the man could appraise the communication values in proposed ads, obtain predicted readership from the model and then use his judgment to make tradeoffs among various criteria. Such man-machine interactions hold high promise for the efficient use of marketing knowledge as summarized in the form of models.

Before leaving advertising, I want to mention some examples of laboratory work. In certain cases laboratory work has immediate decision making implications whereas in others it promises deeper understanding of processes that may lead to better decision models. My two examples are in the latter class. Wells and Chinsky [72] have played sequences of digits to people on earphones and then asked them to choose a digit. The sequence may be regarded as a set of idealized messages and the choice an idealized "brand" selection. Various characteristics of the sequence can be changed, e.g., percentage of each digit, placement of certain digits near the beginning or

end, and the use of periods void of a given digit interspersed with high rate periods. Such characteristics are found to affect the choices made in interesting and suggestive ways. Krugman [44] is using a method to appraise a person's interest in a picture or other visual display by measuring the size of the pupil of the eye. He shows encouraging indications that these measurements may be more predictive of sales than answers from questionnaires. We can expect laboratory methods to be increasingly helpful in developing models and providing data for operating systems.

Sales Force. The study of salesmen and the sales force has been less active than the studies of advertising, at least in terms of published data based models. One well known study is that of Brown, Hulswit, and Kettelle [10]. They performed an experiement in which the level of salesmen's effort was varied to determine its effect on sales. With this in hand they developed a model for allocating effort to customers. Buzzell [12, (Chapter 7)] reports a case study done by an in-house OR team. A central question was the allocation of salesmen's effort between wholesale and retail channels. The team took a fresh look at the accounting methods used to assess salesman profitability, redetermined sales potentials by area, and developed an allocation model. The redesigned system was striking in that it reversed the previous emphasis of effort between channels. These two studies are examples of allocation of salesmen's effort, a class of problems which has been approached rather successfully.

Farley [25] has a model for determining a commission structure for salesmen. The model is not data based, but his main point is reasonably data independent. He argues for a compensation plan that makes commission

the same proportion of gross profit on each item in the product line. Then, it can be shown that when a salesman allocates his effort to maximize his own income, he is also maximizing company profit.

Channels of distribution. We first mention a descriptive simulation and some physical distribution studies oriented toward cost reduction. Balderston and Hoggatt [4] have simulated in some detail a market involving suppliers, wholesalers, and retailers, patterned after the Pacific Coast lumber industry. Emphasis is given to the role of communication, including its cost, and to the nature of preferences built up between wholesalers and suppliers and wholesalers and retailers. The authors study the evolution of the market under a variety of structural assumptions.

Considerable work has been done on physical distribution. Gerson and Maffei [31] describe a good sized distribution model and a partial optimization procedure for it. The goal is to assign customers to warehouses and then factory output to warehouses so as to minimize total cost. Kuehn and Hamburger [45] have a heuristic program for locating warehouses. The objective again is to meet demand at minimum cost.

Turning now to studies of factors that affect sales and that are also decision oriented, we discuss two studies, one related to market expansion, the other to site location.

Hartung and Fisher [32] have made a striking empirical discovery, built a simple model to try to explain it, and have showed how to use the model to plan market expansion. Their discovery is that for the retail outlets of a particular industry, the petroleum industry, average sales per outlet in a city increases with the market share of the parent company in the city, at

least over a non-trivial range of market share. This result has strong implications for distribution strategy because it implies a great advantage to concentration of effort. A simple Markov model suggests an explanation: people switch brands of gasoline from time to time. The probability of switching to a brand would be expected to increase with the number of outlets of the brand. As a good approximation over the desired range, the relation can be assumed linear. Under this assumption the solution of the Markov chain equations gives steady state market share expressions that display the observed phenomenon. The expressions are fit to market data to estimate values for unknown parameters. Finally the expressions are imbedded in a marketing planning model that can be used to determine expansion strategies. The study is a particularly happy combination of observation, model and optimization.

The work of Hlavac [39] illustrates some further points. He has constructed a geographic model of an urban automobile market. The model is competitive: each dealer of each car make is thought of as exerting a pull on each prospective buyer. The probability that buyer purchases at a given dealer is taken to be the dealer's share of the total pull on the buyer. The pull is hypothesized to fall off exponentially with distance from dealer to buyer. The pull also depends on the car make of the dealer and on the brand loyalty of the buyer. Each dealer is characterized by two parameters. One of these expresses how effective he is in his immediate neighborhood and may be thought of as reflecting good service, good neighborhood relations, etc. The other parameter expresses how fast his sales fall off with distance and reflects his city-wide advertising, his reputation for price-dealing, and other longer range effects.

The model has been fit to 3 months of new car registration data for Chicago, about 47,000 cars. The fit determines the two parameters for each dealer. After fitting, the model will calculate a market share for each dealer in each of 150 geographical areas. The model can be used to predict the effect of dealer changes, for example, the addition of a new dealer, the removal of an old one, or a move in location. It must be kept in mind that such predictions are based on a static model and do not consider, for example, the time for a new dealer to get established. However, this type of model seems far more realistic as an indicator of the potential sales in a neighborhood than most in current practice, since the calculation considers the gross potential of each area, the customer brand preferences, and the location and strengths of competitive dealers.

The model has been programmed for on-line use with the time-shared computer system of Project MAC at MIT. The user can sit with a map of the city, propose a new dealer of a given make in a given area, specify parameters for the dealer, and learn immediately the model's prediction of the effects. After each request the computer in a very short time recalculates market share for every dealer in every area and, on command, will print out any of a variety of information. For example, the user can ask for the predicted sales of a new dealer, how many sales are expected to come from each area, how many are expected to come from dealers of the same make, and how many from competitive makes.

Conceivably, one could use the model to work out a mathematically optimal pattern of dealers over the city or, more modestly, the optimal location of the next dealer. However, current thinking is moving away from this type

of analysis in its strictest form. Conversational computer programs hasten the trend. A decision on a new dealership involves many factors not included in the present model: the availability of property, financing, the managerial capabilities of the proposed dealer, and the micro-geography of each proposed location (streets, frontages, etc.). Perhaps some of these factors can be modeled but, as of now, they are not. Yet we do not have to wait to take advantage of present knowledge. A person can have at his fingertips the model's estimates of sales for any location and can weigh this information in with more subjective factors.

Let me cite another important feature of on-line models. For the first time, I believe, a manager can really assimilate a model and its implications in an adequate way. Passive slides, charts, and tables never quite seem to do the job. However, when a person can interrogate the model, receive a response, let it give rise to another question, and immediately re-interrogate, he is able to build up a far more satisfactory feeling for what the model is doing. We can expect that some models will behave counter to the intuition of experienced marketing professionals and the the diagnosis of the reasons will be an important form of feedback for improving model quality.

Pricing. In this area we cite a simulation, a Bayesian analysis, a laboratory technique, and a pair of econometric studies. The simulation is Cyert, March and Moore's [20] work on department store pricing. Theirs is a descriptive model that shows in impressive detail how a given department store sets its prices. Price predictions are usually good to the penny. Such a model is very sobering to the normatively inclined for it shows the detail required for an adequate description of a real process. Yet a study

of this type is obviously an ideal starting point for improving a process.

Green [12, (Chapter 6)] describes a Bayesian pricing study for an industrial product. The work illustrates two of our initial points: the use of subjective information and the handling of considerable complexity. He segments the market and then obtains subjective probabilities of market penetration in each segment under various proposed prices and at various points in time. In addition, estimates are made of the probability of various competitive responses to each price change. The analysis is laid out as a decision tree whereby the proposed pricing strategies can be evaluated. The formulation and analysis of problems in decision tree form has been a methodological innovation that has rapidly found considerable favor.

Pessemier [64] has developed a laboratory technique for measuring a type of price elasticity. Subjects make "simulated shopping trips" in which they make brand selections in a given product class. The relative prices of the subject's customary brand and the competing brands are varied to see at what price difference the subject switches. Pessemier [65] has gone on to propose a Markov model that would use the elasticity information in an evaluation of possible price changes.

As a final example of work in pricing, Massy and Frank [57] and Telser [68] have studied the effects of price changes and cents-off deals in market share. They try to measure elasticities by using regression methods on consumer panel data. Telser's work is somewhat limited in that he does not differentiate between a deal and a change in shelf price. To a manufacturer these are quite different actions. Massy and Frank separate the

effects but their data and mode of analysis do not permit a direct comparison of relative efficacy. Massy and Frank, however, study the way price and deal effects are spread over time and how they differ among market segments defined (1) by a brand loyalty measure, (2) by package size, and (3) by store class. Consumer panel data offer a fine opportunity to study deals, but it is not at all clear that econometric methods are the appropriate ones. The model building techniques of Morrison [61] and Montgomery [60], although not directed by them at questions involving deals, seem to offer more promise.

New Products. Just about every company is actively engaged in bringing out new products. A variety of techniques have been developed that support this activity. PERT methods are applicable and are being used in various places without fanfare. Experimental design methods are useful in test marketing and have been discussed by Lipstein [54], who has also proposed Markov chain analyses to accelerate the acquisition of information in test marketing [53]. Charnes, Cooper, Devoe, and Learner [15, 16, 17,18] have proposed a mathematical programming model to treat certain decisions in new product introduction.

A particularly fruitful way to analyze the sequence of decision involved in new product development and introduction is to formulate the problem as a decision tree [1 (Chapter 8), 55]. Closely related and relevant is the technique of risk or venture analysis [2, 36, 37]. These techniques are not restricted to new product problems but are general frameworks for decision making under uncertainty.

In risk analysis a set of alternative plans are laid out, the problem being to choose the best. Cost and revenue forecasts are made, with uncertain elements being described by probability distributions. The operation of each plan is then simulated using random choices for uncertain events. Repeated simulation gives a probability distribution of outcomes for each plan. These can be compared for expected value, probability of loss, and other characteristics. The decision maker selects the plan that best suits his criteria.

Decision trees are designed to handle the sequential and conditional aspects of choice processes. Thus in Green's example [1] of new product development, the process goes through three possible review stages: pilot plant, semiworks, and full commercial plant. At each stage several choices can be made. The process usually involves chance events. Decision points and chance events become forks in a tree diagram representing all possible evolutions of the process. The tree can be analyzed by starting at each final outcome and working back, finding the best decision at each decision point. Green presents a case history that shows the interplay between an analysis and its implementation.

These techniques are general frameworks for analysis. A great deal of digging for data and careful thought are required to obtain a good result. The frameworks are proving very useful, however, particularly when illustrated by a case study. They guide the data search and show what to do with data once obtained.

Toward the Design of Marketing Systems

We have reviewed some of the current quantitative work in the functional areas of marketing. But these areas should not be treated in isolation -- the whole concept of the marketing mix is that the functions interact. We need models that encompass several areas at once and account for their interdependence. Furthermore these models should be responsive to changing market conditions. Thus, we really want to be able to design marketing control systems.

A marketing control system can be viewed as the set of activities shown in Figure 1. A company assembles a variety of marketing data: its own sales, competitive sales, surveys, distribution data, media data, etc. into a marketing information system. The company, or various individuals within it, have conceptions about how the market works. We shall call these models. They may be qualitative and perhaps only partially articulated. However, anyone who makes decisions or argues a position must have a set of beliefs about how the market works and we shall call this his model. Then too, of course, the company may have explicit quantitative models.

The acquisition of new information leads to the creation of new models, the modification of old ones, and, the updating of parameters in the existing ones. On the basis of the models, individuals and groups within the company set values for marketing variables, i.e., decide on budgets, choose media, allocate salesmen's effort, etc. In addition, to a degree that varies considerably from firm to firm, a company will install measuring devices to monitor the company's and the competitor's marketing activities. Usually

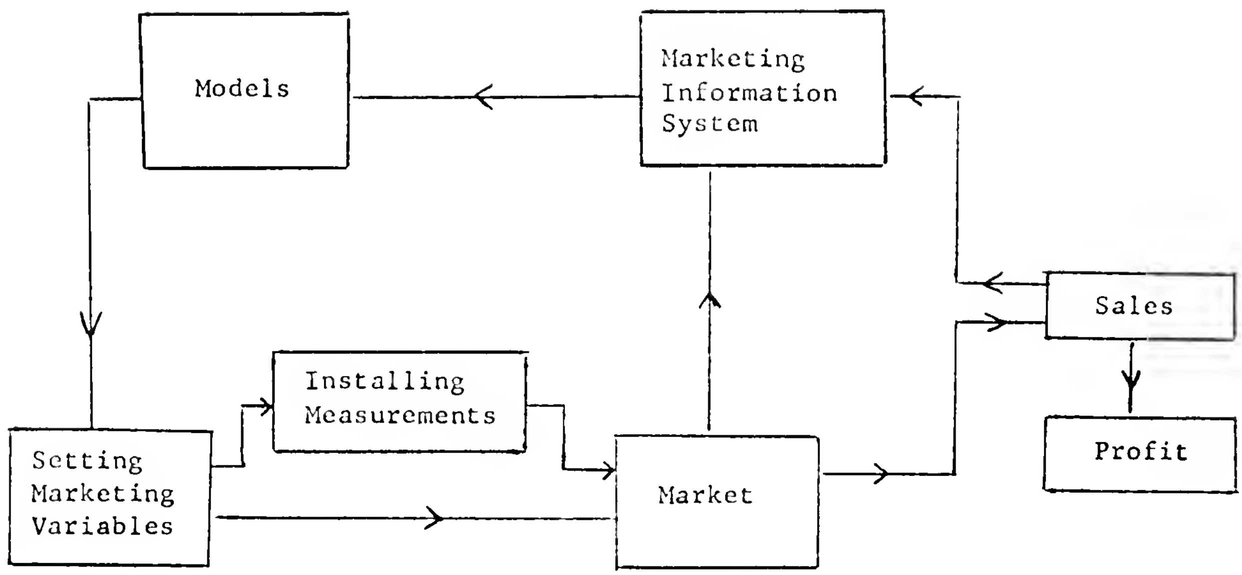

Figure 1. A Marketing Control System

these devices simply record what happens without special attention to developing information about what would have happened had different decisions been made. However, in some instances, attempts are made to make measurements of the latter type. We shall call them response measurements.

After these tasks have been completed, the market responds, sales are produced, and so, hopefully, are profits. Sales, regarded as information along with other data from the market are fed back into the marketing information system and the cycle repeated.

Obviously every company has some procedures by which it sets its marketing variables but usually the models and methods are not formally specified. Our interest is in ways that formal quantitative methods can assist the process. Current work is still fragmentary and largely uncoordinated but some developments are worth mentioning.

Adaptive systems. The need for adaptive systems in marketing has frequently been recognized in a qualitative way. For example, Robinson and Luck [67] have an eight step "Adaptive Planning and Control Sequence". In the quantitative line, some of the Bayesian decision tree models of Green [1] may be considered adaptive since certain future decisions depend on information developed as the process unfolds. Kotler [43] includes some adaptive rules in his simulation of a market during new product introduction.

Some of my own work [50] has been concerned with adaptive control of promotional spending in an ongoing situation. This is in contrast to the above models which are primarily concerned with new product introduction. In the model of the ongoing situation the effect of promotion on sales is allowed to change with time in a probabilistic fashion. Information about

promotional effectiveness is collected in each time period by performing a multiple market sales experiment. The results of the current experiment are combined, in a Bayesian manner, with prior knowledge of effectiveness to give a best current estimate. Then promotion rate is set so as to maximize future expected profits. Finally, a new experiment is designed to restart the feedback cycle.

A numerical example using realistic estimates of key parameters is studied analytically and by simulation. One suggestive result is that the adaptive decision rules developed for one situation seem to work quite well for reasonably different situations. The key to good operation appears to be to make some kind of objective measurement even if it is not too precise and to let the measurement influence operations, but not in a dramatic or unstable way.

Marketing Information Systems. A good marketing information system is essential for effective marketing operations, whether or not explicit quantitative models are used. By an information system we mean an organized assemblage of data that is regularly collected and stored in easily retrievable form. For companies of any size we can restrict our attention to computerized systems.

Most companies have computerized their order processing and billing. Out of this has usually come a spinoff of sales statistics, although if the company is a manufacturer, the sales are ordinarily factory shipments and so are removed from the final user in an important way. In any case, at least for the company's direct customers, it is possible to create a

detailed file of disaggregated data on the who, what, when, and where of sales. Some companies are doing this.

Much more data is available or could be made available for inclusion into data banks and retrieval systems. For example, salesman call records, advertising insertions, warranty and service data, consumer panel data, media information, store audits, and dealer records. In some cases competitive information can be collected. By and large, data banks in these areas are few and far between. Some specialized banks do exist. Chrysler for example, has an extensive bank of service data on individual cars to go with its five year warranty.

One reason that data banks are not yet more extensive is that people ask, not unreasonably, what the data can profitably be used for. The answers presumably lie in the models and variables-setting areas of our control system. Yet model builders frequently suffer from lack of adequate data with which to build and test models. I am not pessimistic about this. We can expect an evolution of data suggesting models, models suggesting further data, etc. An evolution rather than a revolution is also indicated as the way to proceed in the face of changing computer technology.

One point has become clear, however. There is great advantage in saving data in disaggregated form, e.g. in billing, the individual transaction information of who, how much, what items, what price, etc. The technology is available to handle such files. Once established they represent what may be called a flexible fixed asset. They have the same advantages over an aggregated file that a digitally controlled machine tool has over a special purpose one. When new needs arise, a reprogramming permits

a new application, which might otherwise be virtually impossible. With a file of disaggregated sales data, it is possible to go over past history and simulate a different kind of operation. Thus one might ask what would have happened under a different discount structure. Hypotheses could be made about the response of customers by type and size. Then, several years of back operation could be rerun in a simulation to find out the net effect.

The published literature on marketing information systems per se is sparse, although there is beginning to be material available on management information systems in general [23].

Complex models. Let us turn now to the problem of developing models that have somewhere near the degree of complexity that most people feel will be minimal for a reasonable representation of a company, its competitors, its customers, and the economic environment. Perhaps the most extensive work along these lines is that of Amstutz [3]. He offers a general framework for what he calls a total market simulation and has gone on to apply portions of it in specific cases. Barton [6] and Howard [41] also have extensive models, but as yet these are not too specific and so would be hard to describe as quantitative models in the sense being used here.

Amstutz defines five major interacting sectors: the manufacturer, the consumer, the retailer, the distributor, and the salesmen. Each of these elements responds actively to its inputs and generates outputs that affect other sectors. The manufacturer's sector generates inputs to other sectors as a result of manufacturer pricing, promotion, distribution, sales force management, and product policy decisions. In the retail sector the retailer responds to business climate, promotion, and customer actions to develop his

pricing, product line composition, ordering and promotion decisions. The distributor sector encompasses the same function as the retailer plus the allocation and maintenence of a sales force. The salesman model accounts for the salesman's interaction with manufacturer, distributor, and retailer.

The consumer sector is particularly detailed. The consumer makes decisions whether or not to shop, purchase, and generate word of mouth communication. His actions are influenced by his attitudes toward and awareness of each brand. Changes in brand attitudes are governed by a set of more basic attitudes concerned with specific product characteristics, independent of brand. As the consumer is exposed to advertising, word of mouth information and product experience, the basic attitudes control a selective perception of the communications. The perceived communications lead to the formation and change of brand attitudes and awareness.

Such a model requires the estimation of many parameters and the making of many structural assumptions. However, companies have frequently conducted studies about a variety of different aspects of their market and can suggest reasonable parameter estimates. In some companies individuals have been willing to express their judgments about market mechanisms in a form suitable for inclusion in simulation models. Then the separate judgements can be combined into an overall market representation. The model must be tested for its accuracy in representing the phenomena it seeks to describe. One can expect to have to modify and test iteratively to achieve a satisfactory representation at micro and macro levels.

Concluding Remarks

We have reviewed a number of developments in operations research in marketing. Some of them perhaps have a brave new world aura. Still we have tried to emphasize models and methods that can realistically make a contribution to a firm's marketing activities. Several trends are noteworthy. Models are increasing in complexity. They are more frequently data based. Subjective judgments are being explicity introduced into quantitative analyses. On-line computation is bringing models to life and making the knowledge they represent easily available.

One can only expect continued rapid growth.

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